Infrared Physics & Technology 57 (2013) 36–41

Contents lists available at SciVerse ScienceDirect

Infrared Physics & Technology

journal homepage: www.elsevier.com/locate/infrared

Color contrast enhancement for color night vision based on color mapping

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HIGHLIGHTS

- Combination of color contrast enhancement and reference palette techniques.
- Missing values are interpolated using the nearest Euclidean distance.
- The method is validated through objective metrics.

ARTICLE INFO

Article history:
Received 20 August 2012
Available online 8 December 2012

Keywords:
Color night vision
Color contrast enhancement
Color mapping

ABSTRACT

The increasing availability and deployment of imaging sensors operating in multiple spectral bands has led to a large research effort in image fusion, bringing a lot of pixel-level color fusion algorithms. Color constancy and color contrast are two important topics for color image fusion. However, there is no work considering these two aspects in the meanwhile. The paper focuses on enhancing the color contrast between targets and their backgrounds and maintaining the color constancy. Firstly, a group of visible and infrared images are rendered with natural colors with color contrast enhancement algorithm. Then a color reference palette is derived from source images and their corresponding fused results. To enrich this palette, the nearest Euclidean distance determines the absent colors. The complete palette can be deployed in real-time to different multi-band image sequences of similar scenes. Experimental results based on different data sets show that the targets are popped out with intense colors while backgrounds present natural color appearance. Some objective analysis also shows that the presented method not only inherits more detail information from source images but also brings bigger color distance when comparing with the existing algorithms.

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1. Introduction

Image fusion is a methodology concerned with the integration of multiple images into a composite image. It will benefit the image analysis in many fields, such as studies in remote sensing, machine vision, and molecular biology [1].

Until recently a gray or green-scale representation of nightvision imagery has been the standard. However, the increasing availability of multispectral imagers and sensor systems has led to a growing interest in color display of night vision imagery. In principle, people can discriminate several thousands of colors but only about 100 shades of gray at any instant. As a result, grayscale nightvision images are usually hard to interpret and may give rise to visual illusions and loss of situational awareness. However color fused images may improve feature contrast which may bring faster and more accurate object identification, scene understanding and reaction time. Also, observers are able to selectively attend to task-relevant color targets and to ignore non-targets with a task-irrelevant color. Thus, techniques for fusing IR and intensified visual imagery should be employed in order to provide a compact representation of the scene with increased interpretation capabilities [2,3]. A number of techniques have been proposed to render night-time imagery in color [4–8]. A simple mapping of multi-bands into the three components of an RGB or YUV image can provide an immediate benefit. On the other hand, inconsistent color mappings may hinder situational awareness due to lack of physical color constancy [8]. Thus, an image fusion method for night vision imagery must result in color images with natural and stable appearance and a high degree of similarity with the corresponding natural scenes.

In 2003, Toet originally applied global color transferring [9] to render night-time imagery with a natural color appearance [10,11]. This method matches the first order statistical properties of night-vision imagery to those of a color reference image. As long

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http://dx.doi.org/10.1016/j.infrared.2012.11.008

as they are similar to each other to some degree, satisfactory results can be obtained. When the composition of the reference image is different significantly from that of the nightvision image, the result may look unnatural. To overcome this shortcoming and get color constancy, Hogervorst and Toet [3,12] presented a lookup-table technique to optimize the match between the multi-band image and the reference image. Once it has been derived the color mapping can be deployed in real-time to different multi-band image sequences of similar scenes. Although the advantage of Toet's method for situation awareness in real-time application task has been well demonstrated, its effect on target detection is still weak as their methods process all three channel of the color space with the same linear mapping in the color transfer step, resulting in low contrast between the target and the background. So targets that are clear in the IR image sometimes may become invisible and are difficult to detect, that may hinder target detection tasks [13]. Thus, ideal image fusion should not only improve the situation awareness performance but maintain or increase the high detectability of the target in the IR image [14–16].

Image fusion schemes based on image analysis and nonlinear color mapping can easily meet this demand [8,17,18]. Zheng and Ma [8,18] presented a new "local-coloring" method that functions to render the nightvision image segment-by-segment by taking advantage of image segmentation, pattern recognition, histogram matching, clustering and merging techniques. Instead of extracting the color from a single reference image, the statistical properties are from a set of natural scene images. Depending on the scene contents and colors, the targets in the rendering results can demonstrate distinguishable colors while the whole scene possesses natural and realistic coloration. However, regarding computational complexity, the local-coloring method is even more expensive than Toet's original color transform, since it involves time-consuming procedures such as nonlinear diffusion, histogram analysis and image segmentation. Simpler color contrast schemes were obtained by using linear fusion and nonlinear color transferring [13]. Yin and Qian [13,19] introduced a ratio of local to global divergence into color transferring equation. The hot and cool targets both can be popped out with intense colors. However, just like Toet's original method, the reference image must have the similar composition with the false fused image.

Benefitting from Toet's and Qian's methods, here we will introduce a new simple and fast method to consistently apply natural daytime colors to multi-band nightvision imagery when bringing color contrast between the targets and the background. The new method is illustrated in Fig. 1. First, we generate a series of color fused samples using color contrast enhancement approach in YUV color space. Next, a reference color palette is produced from corresponding the source multi-band images and their corresponding fused results. To make it fulfilled, we fill in the absent colors by calculating the nearest Euclidean distance. Once the palette is derived the color mapping can be easily deployed in a real-time application.

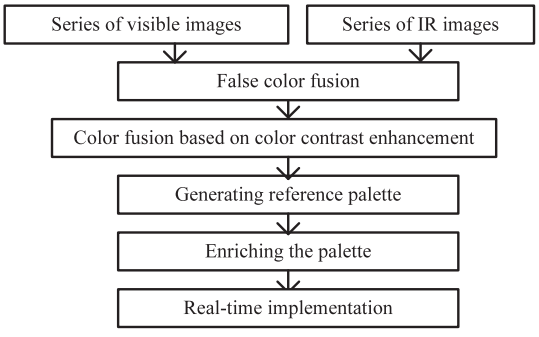

Fig. 1. A typical color image fusion system.

2. Samples based color contrast enhancement

Since combining simple linear false color fusion and nonlinear color transferring can bring good color contrast between the target and the background, we still adopt a similar scheme to produce a group of color fused samples which will be the color sources of the reference palette. Different from Qian's method, the multi-band sensor images are rendered directly in YUV color space. YUV space is commonly used in video transmission and processing system. Y denotes luminance, U stands for difference between blue and luminance, and V represents difference between red and luminance. Image fusion and color transfer in this space will need not iterative color space transformation. Firstly, each pair of visible and infrared images is transformed to a false-color image by taking them as input to the three channels of a YUV image. The false color fusion is carried out as:

$$\begin{cases} Y = I_{vis} \\ U = I_{vis} - I_{IR} \\ V = I_{IR} - I_{vis} \end{cases} \tag{1}$$

where I_{vis} and I_{IR} stand for the visible and IR images, respectively. By mapping the visible image to the achromatic channel, high-frequency information is kept in the fused image. The differencing operation between the visible image and IR image provides inter-sensor contrast. The resulting image agrees with our natural associations of warm (red) and cool (cyan).

The false color fused images have unnatural color appearance and lack of color constancy. In the following step, linear and nonlinear color transfer is implemented to render the false color fused images with natural color appearance and enhance the color contrast between the targets and the backgrounds. In Yin's and Qian's methods some information features (like edges and corners) that are available in the multi-band images may disappear. Especially, in Qian's method, multi-band images are pre-processed by median filtering and then are fused by a weighted method that may both result in weak edges that are apparent in the source images. To maintain these high-frequency information, a strengthening exponent p is introduced into transferring equation in V channel which will further enlarge the color distance between different details. Color transferring equations are described as:

$$\begin{cases} Y' = \frac{\partial_\gamma^Y}{\partial_f^Y}(Y_f - \mu_f^Y) + \mu_\gamma^Y \\ U' = \frac{\partial_\gamma^U}{\partial_f^U}(U_f - \mu_f^U) + \mu_\gamma^U \\ V' = w \cdot \frac{\partial_\gamma^V}{\partial_f^V}(V_f - \mu_f^V) + \mu_\gamma^V \end{cases} \tag{2}$$

where w is defined by luminance distance in IR image between each pixel $IR(i,j)$ and the average luminance value μ_{IR} as:

$$w(i,j) = ||IR(i,j) - \mu_{IR}||^p / \langle dist \rangle \tag{3}$$

$$\langle dist \rangle = \sum_{i=1}^{M}\sum_{j=1}^{N} ||IR(i,j) - \mu_{IR}|| / M \times N \tag{4}$$

As both hot and cold targets are of great divergences from the mean intensity of the IR image, both of them can be enhanced. With color contrast enhancement, hot targets will appear intense red, while cold targets will appear cyan in the fused images. The red color of hot targets can alert observers of possible danger, and the cyan color can help observers to detect cold targets or low temperature regions [13].

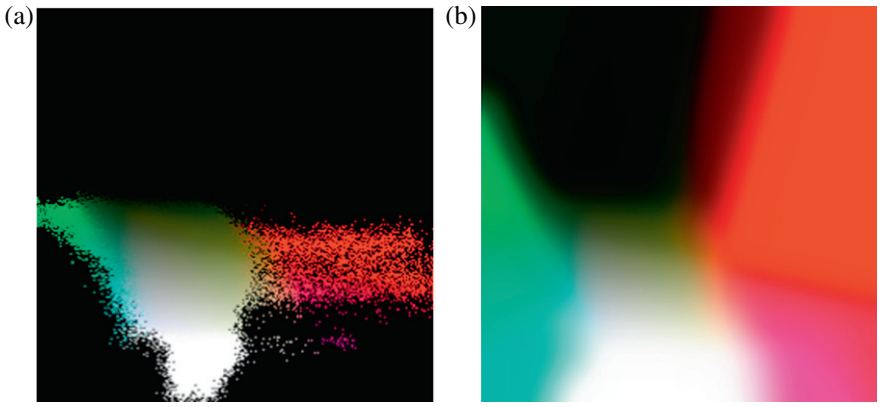

Fig. 2. Reference palette from NV4917 pairs: (a) non-amended palette (b) amended palette.

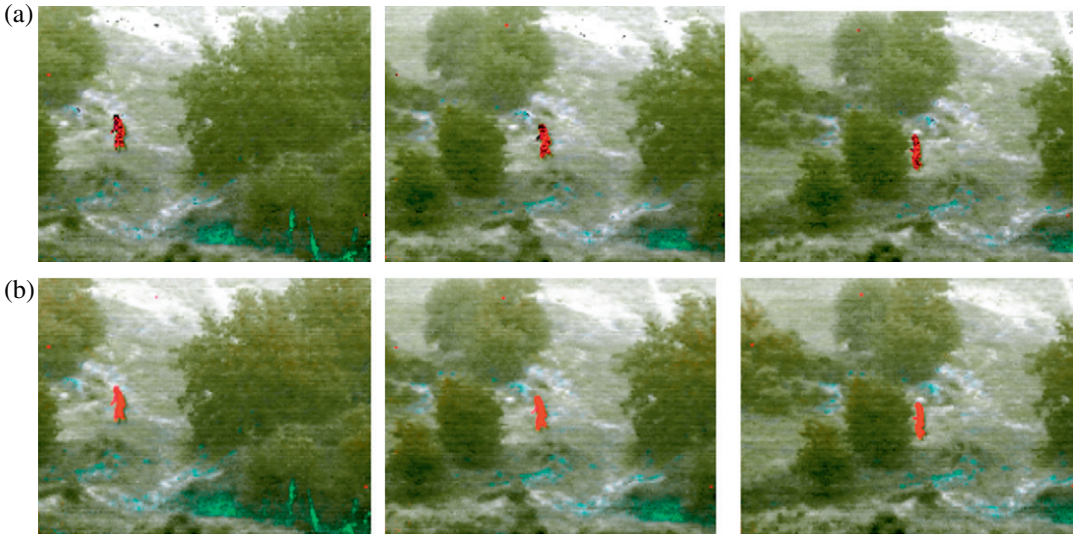

Fig. 3. Color mapping based on the palette. (a) Color mapping with Fig. 2a. (b) Color mapping with Fig. 2b.

3. Color mapping based on reference palette

As the statistical approach inherently only addresses the global color characteristics of the depicted scene, there is no strict relationship between sensor output values and object color. Similar to lookup tables, here we will describe a fixed color transformation that makes object colors determined by multi-band sensor values. In this approach color mapping is derived from a subset (or all possible) multi-band sensor outputs. This (sub)set of multi-band sensor outputs forms the reference set. The color attributed to any multi-band sensor value is equal to the color corresponding to the reference sensor output that is most similar to the actual sensor output. To achieve this, a reference palette is built based on a set of samples for which both the reference sensor outputs and their corresponding natural fused colors (YUV-value) are known. It can be defined as a matrix **P**:

$$\mathbf{P}[i,j] = (R(i,j)\ G(i,j)\ B(i,j)) \tag{5}$$

where i and j separately denote the visible and infrared sensors output values changing from 0 to 255. $R(i,j)$, $G(i,j)$ and $B(i,j)$ are final natural rendered colors.

To obtain the final natural colors with coordinate (i,j), first, the pixels with gray values i and j are located in each set of visible and infrared images separately. Then finding all corresponding pixels in their exactly corresponding natural fused results. Next, we calculate the average YUV-vector over this ensemble of pixels. Finally the resulting average values are transformed back to RGB. This process yields the matrix containing the natural colors associated with the distribution of the pixels: colors that appear more frequently are attributed a greater weight.

Unfortunately, we cannot find enough multi-band images to cover all possible 256×256 combinations, so the rendered results tend to include some undesired black points when applying the reference matrix to the infrared and visible images with similar scenes. To promote the reference matrix, we calculate the Euclidean distance between the absent combinations and the existed multi-band sensor values. And the nearest match determines the absent RGB-values. Once the full reference matrix has been defined, it can be used in a real-time application. And the color of objects depends only on the multi-band sensor output values and is independent of the rest of the image content.

4. Experimental validation

4.1. Visual assessment

To validate the effectiveness of our method, we select two groups of multi-band image sequences provided by Alexander Toet and TNO Human Factors Research Institute and compare

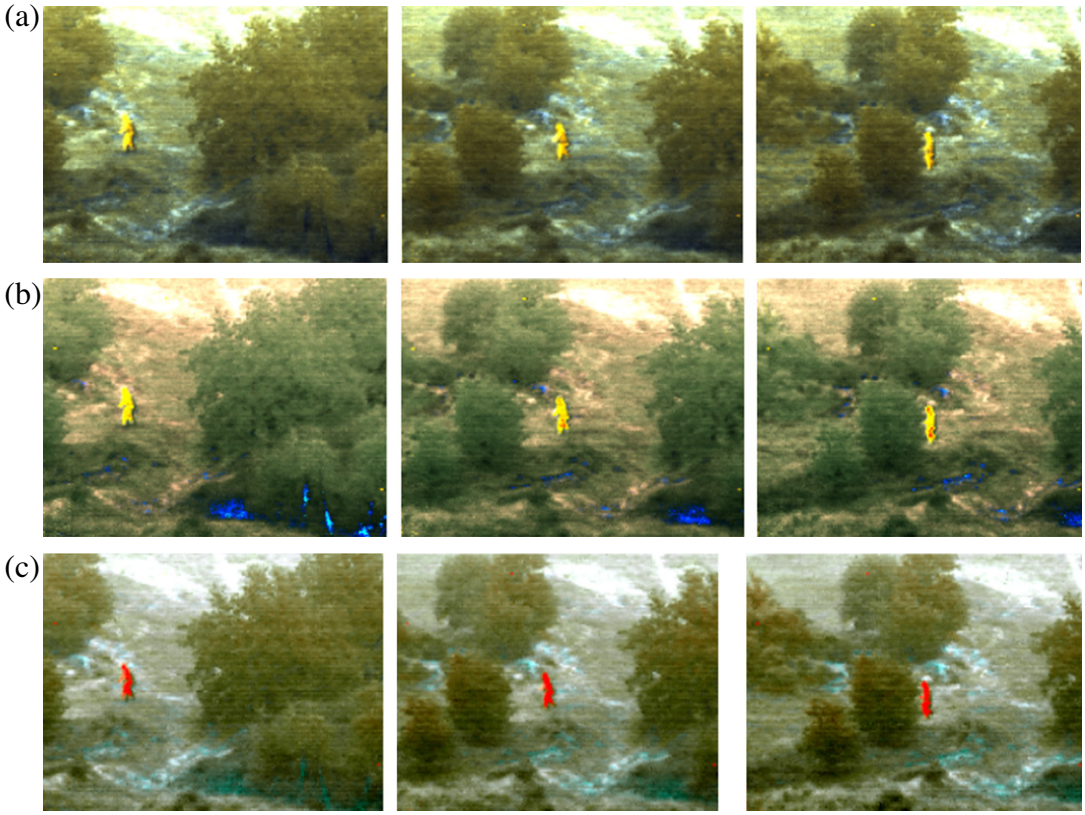

Fig. 4. Fused results without and with enhancement. (a) Fused results without enhancement. (b) Qian's fused results. (c) Yin's fused results.

subjectively our fused results with those brought by Toet's method [10] without enhancement and by Yin's and Qian's enhancement methods [13,19].

In the first experiment, we randomly select 16 pairs from NV4917 to produce reference palette and the rest three pairs are tested using the generated palette. Figs. 2 and 3 show the reference palettes generated from 16 pairs and the corresponding mapping results. Because 16 pairs cannot cover all gray levels, the palette presents many black points (seen in Fig. 2a); When we directly map it to three pairs of multi-band images, hot target cannot be rendered effectively which can be seen in Fig. 3a. To overcome this shortcoming, we adopt the minimum Euclidean distance to compensate the absent points. Fig. 2b gives the amended palette and Fig. 3b well show the overall rendered effects.

Fig. 4 demonstrates the comparative fused results. Fig. 4a are colorizing results without color contrast enhancement. Fig. 4b and c are corresponding enhanced results brought by Qian's and Yin's methods separately. Obviously, Qian's, Yin's and our rendering effects can all pop out hot targets. The man appears intense red or yellow[1]. When comparing with Qian's method, tests show that details such as brooks in the foreground are clearer and more apparent in Yin's and our results, while part of them is covered by grass in Qian's method. It is because that in the equation of false fusion, the IR and visible images are both mapped to the achromatic channel by a weighted method. That can get bigger targets' area but it is at the cost of losing details. In addition, the overall color is milder in our rendered results. While some areas in Qian's effects are very dazzling which probably reduces the comfortable level of observation. When comparing with Yin's fused results, the man become bigger and more integrated. In addition, the details are clearer and the backgrounds can present more natural colors in our result.

The same conclusions can be deduced from experiments using NV7404 pairs. In this testing, 17 pairs are used to produce reference palette. Using three remaining pairs, Fig. 5 gives comparing effects brought by different methods. Without channel's enhancement the man is hard to distinguish from the background (e.g. Fig. 5a). Other three methods all provide better results (seen in Fig. 5b to d). The man appears red and intense orange–yellow, thus can be easily distinguished from the backgrounds. In addition, our method (Fig. 4d) not only pops out the target but also brings more natural and clearer backgrounds.

4.2. Objective assessment

In many applications, the end user of the fusion result is a human, thus, the human perception of the composite image is of paramount importance and therefore, fusion results are mostly evaluated by subjective criteria. Objective performance assessment is a difficult issue due to variety of different application requirements and the lack of a clearly defined ground-truth [14,20]. Fortunately, there have been some effective performance measures according to specific tasks such as the percentage of correct classifications, false-alarm rate and color distance. Here, we mainly aim at improving the identification ability of the targets by enhancing the color contrast between targets and their surrounding backgrounds, so we are interested in evaluating different color fusion methods through color distance. In addition, we are also interested in measures that express the successfulness of fusion techniques that create a composite image that retains salient information from the source images while minimizing the number of artifacts or the amount of distortion that could interfere with interpretation. The following will gives these measurements.

[1] For interpretation of color in Fig. 4, the reader is referred to the web version of this article.

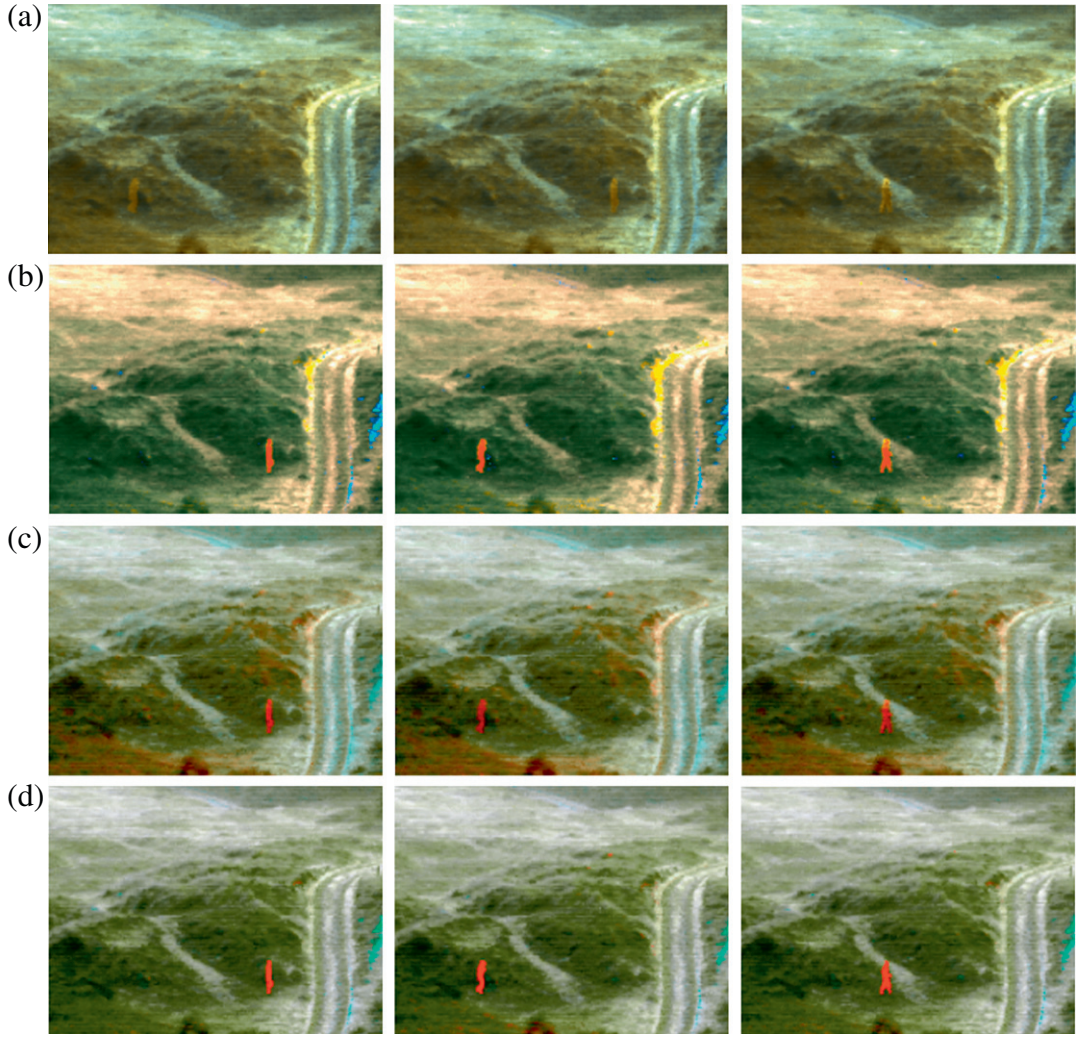

Fig. 5. Fused results of different methods. (a) Fused results without enhancement. (b) Qian's fused results. (c) Yin's fused results. (d) Our rendering results.

The hit rate of color vision in detecting a target relies mainly on its ability to characterize color [21]. When the target is far from the background in color, it improves the object-background discrimination. So we measure the color distance between the target region and its surrounding region. Since image signals are generally non-stationary, it is appropriate to measure the color distance between the target region and its surrounding region over local regions and then combine the different results into a single measure. We use a sliding window of fixed size which moves from the top-left corner to the bottom-right corner. For each window w, the color distance is computed by:

$$D(t,b|w)=\sqrt{(\langle Y_t\rangle-\langle Y_b\rangle)^2+(\langle U_t\rangle-\langle U_b\rangle)^2+(\langle V_t\rangle-\langle V_b\rangle)^2} \tag{6}$$

where t, b stand for the target and the background regions, respectively. $\langle\rangle$ is the mean value.

And the overall image color distance is defined by averaging all local distances:

$$D(t,b)=\frac{1}{|W|}\sum_{w\in W}D(t,b|w) \tag{7}$$

where W is the family of all windows and $|W|$ is the cardinality of W.

Color distance only evaluates rendering results themselves, and cannot assess how well the results retain the information of the source images. Piella [20] introduced an effective method to measure the similarity of two images. The formula is as following:

$$Q(A,B)=\frac{\sigma_{AB}}{\sigma_A\sigma_B}\cdot\frac{2\overline{A}\overline{B}}{(\overline{A})^2+(\overline{B})^2}\cdot\frac{2\sigma_A\sigma_B}{\sigma_A^2+\sigma_B^2} \tag{8}$$

where σ_A and σ_B are standard variance of images A and B, respectively. σ_{AB} is their covariance.

$$\sigma_A=\sqrt{\frac{1}{MN-1}\sum_{m=1}^{M}\sum_{n=1}^{N}(A(m,n)-\overline{A})^2} \tag{9}$$

$$\sigma_{AB}=\frac{1}{MN-1}\sum_{m=1}^{M}\sum_{n=1}^{N}(A(m,n)-\overline{A})(\overline{B}(m,n)-\overline{B}) \tag{10}$$

In formula (8), the first component is the correlation coefficient between images A and B, which measures the degree of linear correlation between these two images. The second factor corresponds to a kind of average luminance distortion. The third component measures a contrast distortion. The bigger this value is, the more similar the two images are. As the rendered results are from infrared and visible images, we need to consider the fusion quality of two source images with fused result. Here the relation function of them is reconstituted as:

$$Q(A,B,F)=\lambda Q(A,F)+(1-\lambda)Q(B,F) \tag{11}$$

where A, B and F respectively stand for visible, infrared and fused images. $\lambda\in[0,1]$ is a weight coefficient, which weighs the contribution of two source images to the fused result.

Table 1
Color distance (s).

	The first group			The second group		
	1	2	3	1	2	3
D_{Yin}	160.7399	180.4722	178.2415	146.1892	136.0798	149.8006
D_{Qian}	197.6560	186.4178	178.7850	167.8713	154.9974	169.0587
D_{our}	201.8396	203.4562	205.1244	190.1020	184.1719	190.9615

Table 2
Inheriting information (s).

	The first group			The second group		
	1	2	3	1	2	3
Q_{Yin}	0.5241	0.5095	0.4826	0.5108	0.5085	0.5086
Q_{Qian}	0.4981	0.4762	0.4456	0.4793	0.4759	0.4735
Q_{our}	0.5341	0.5199	0.5041	0.5221	0.5181	0.5180

Table 3
Running time (s).

	Toet's (2003)	Yin's	Qian's	Our method
The first group	0.9612	0.7917	1.0540	0.6102
The second group	0.9467	0.8141	0.9802	0.6123

Table 1 shows the comparison of color distance among three enhancement methods. Qian's and our methods bring bigger color distance due to the strengthening factor that further enlarges the distance of different details to the mean color value. In addition, the intense red colors and more natural backgrounds brought by our method make the color distance improve about 40% than the Yin's.

Table 2 gives the comparison of inheriting information from the source images. It can be seen that Qian's method shows the worst performance because some details are lost by the weighted method. While Yin's and our methods can relatively maintain these information well.

The effectiveness of the proposed method can be further explained through the running time. Table 3 gives the average running time of the three fused results for different methods on a Intel (R) CoreTM 2 Duo 1.50 GHz CPU and 1 GB memory using MATLAB code. It can be easily seen that the proposed method is the fastest. Because it only need simple color mapping and avoid false fusing and color transferring once the reference palette is produced.

5. Conclusions

An improved color image-fusion scheme is presented by combining a color contrast enhancement approach and a palette technique. Color contrast enhancement approach helps to produce a series of color fusion results, where hot targets will appear intense red and cold targets will appear cyan under the control of an enhancement ratio in accordance with the characteristics of the target and the background in IR image. Then the palette is generated from a set of multi-band night-time images and their corresponding fused results. To obtain a complete palette, the nearest Euclidean distance determines absent colors. Once it is established, the method allows for a real-time software implementation that requires a minimal amount of computer processing.

Acknowledgments

This study is supported by China Postdoctoral Science Foundation (Grant No. 20110491415) and Technology Project of Civil Aviation Administration of China (Grant No. MHRD201124). Many thanks to Alexander Toet and TNO Human Factors Research Institute for providing the source IR and visible image sequences that are publicly available online at http://www.imagefusion.org.

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